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Attentional Neurocomputing

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ABSTRACT

Our ultimate goal is to develop neural-like cognitive sensory processing within non-neuronal systems. Toward this end, computational models are being developed for selectively attending the task-relevant parts of composite sensory excitations in an example sound processing application. Significant stimuli partials are selectively attended through the use of generalized neural adaptive beamformers. Computational components are being tested by experiment in the laboratory and also by use of recordings from sensor deployments in the ocean. Results will be presented. These computational components are being integrated into a comprehensive processing architecture that simultaneously attends memory according to stimuli, attends stimuli according to memory, and attends stimuli and memory according to an ongoing thought process. The proposed neural architecture is potentially very fast when implemented in special hardware.

1. INTRODUCTION

Much of the processing that happens in the brain is concerned with stages of perceptual organization for the sensory systems. These include selection processes that support the brain's ability to perceptually separate and attend partials of sensory excitations (that may possess a high degree of relevancy to a task) from within a composite response[1]. In an effort to formulate applicable models for sensory field responsive attentional mechanisms, augmented Kohonen and Hopfield type organization and optimization processes have been embraced to support adaptive beamforming constructs[2,3,4] . Following the popular metaphor, these products are called "neural" adaptive beamformers (NABFs). It is suggested that these are generalizable to function as fundamental building blocks in models of sensory processing, serving as instantiations of a general adaptive beamforming (ABF) paradigm that is useful for understanding and producing computational correlates of cognitive sensory systems. The beamforming paradigm easily integrates the qualities of attentiveness and binding when it is applied to primitive partials of sensory excitations. **It emphasizes a neural coding that is based upon comparison of temporal patterns arriving on spatially separate channels. For example, beamformers participate in the transformation of temporal codes to spatial codes, i.e., they produce the effect that temporal patterns that arrive on separate channels are capable of activating specific loci in a neuronal layer based on their relative activity.**

Ultimately, the fundamental paradigms of the applied models must support a minimal set of functions which compose a comprehensive computational system capable of autonomously generating percepts. The literature on phenomenological and physiological studies of sensory systems of the brain[5]suggests that a desirable object orientation on the part of the brain is supported by continual interaction between computations occurring within somewhat specialized though interdependent nuclei. This process often includes the integration of different sensory modalities. However, even within a single modality there is considerable interactive integration. It can be said that cognitive sensory function in general encompasses the simultaneous acts of (1) attending memory according to stimuli, (2) attending stimuli according to memory, and (3) attending stimuli and memory according to an ongoing "thought process." Thus, attentional focussing is a key element of the cognitive sensory act. The thought process is a director of efference or exemplar generation that expresses an object hypothesis during performance of a task or

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during "visualization," i.e., during planning or anticipation, and it is a [illegible] of attentional [illegible] over sensory processing.

As an application of the general concepts discussed here, a sound processor is being developed that is designed to be, in many respects, a computational correlate of animal auditory systems. This work is particularly germane to sonar system development and voice command systems. It is also relevant to signal processing and communications in the electromagnetic domain through application of its underlying principles. Similarly, analogous effects are found in phenomenological studies of the human visual and auditory systems, suggesting that there are pervading computational paradigms at work across the sensory modalities[6].

2. MECHANISMS

2.1 Encoding

What contribution to the computational model will the proper encoding of the stimulus provide? Biological systems make extensive use of encoding transformations. Considering the auditory system in this respect, one finds the immediate spatial expression of the spectral content of an excitation along the basilar membrane. This mapping is encoded into the common language of sensory and cortical neurons at the hair cells. This common language, in combination with the capability of neurons to learn and spontaneously generate bursting patterns gives rise to invariant feature representations, efference, attentiveness, memory, a retained model of the world, and ultimately consciousness.

In our model for cognitive auditory processing, the ability to form an impression of an object, i.e., to recognize an object by some relatively invariant quality of the sound it makes, will be emphasized. In order to achieve a frequency-shift-invariant recognition of a source of sound, thereby emphasizing timbre over pitch for recognition purposes, the encoding such as is done by the *basilar membrane and hair cells* is essential. The frequency content of each partial is represented by place in the tonotopic arrangement. For computational purposes, the phase is encoded in the quadrature coding discussed under **2.2 Timing and phasing**. Thus it is only necessary that the temporal pattern of the propagating excitation represent the amplitude of the partial as a function of time. As a NABF adaptively weights the incoming partials, it can select a group of responses out of the tonotopic arrangement that exhibit the correct relative patterns of amplitude versus time as being representative of a particular timbre or quality of the sound that is recognizable independent of pitch. Thus the recognition of a musical instrument can be achieved independent of what note is being played; the train whistle can be recognized independently, to a significant degree, of the current Doppler effect (or by using the Doppler effect to advantage because the frequency modulation itself will be a recognizable quality[7]).

This encoding seems to be achieved in the auditory system through the physiology of the hair cells, their stereocilia and links. The rectified charge flow rate representation of amplitude is summated (integrated) and the rate of cell potentiation is reflected in the rate of firing of the cell. The relationship between the firing rate and the stimulus amplitude may have statistical properties dependent upon stimulus noise or internal neural noise as in the stochastic resonance phenomenon[8].

2.2 Timing and Phasing

The fundamental ability to manipulate timing is important in encoding and selection schemes. Within neuronal tissue, an innate ability to support propagation speeds and latency periods over wide ranges exists as part of the chemistry of the physical mechanisms. To enhance the modeling of the timing action of the computational network, both in-phase and time-lagged or phase-shifted versions of the inputs are presented. This gives the network the ability to operate in a quasi-analytic domain.

It is thought that in the auditory processing of many biological organisms an initial spatial mapping is accomplished by introduction of propagation time lag and neuronal response latency. If the relative time lag in the processing is reversed from that produced by the spatial arrangement of the sensors for a given angle of incidence, then the excitations will be added in-phase resulting in a maximum response for that angle of incidence. Simple time lag is very effective in spatial processing for broadband signals and produces appropriate phasing across all frequency components of a stimulus simultaneously. Also, if the stimulus is an aperiodic waveform then there is no response ambiguity versus angle, i.e., there is only one processing time lag that produces the maximum correlation.

Concerning spatial mapping, and as a matter of computing convenience, the question arises whether under certain circumstances the timing quality of neural interaction may be modeled by phasing, i.e., by a quadrature hybrid technique for each frequency band or auditory fibre. It seems that in the case of the auditory system in humans, the distance between the ears is approximately half a wavelength in air for 1000 Hertz. Therefore, the maximum internal delay that would be necessary to compensate for propagation time differences would be less than half a period of the 1000 Hertz wave in air as long as spatial mapping is restricted to fibers responding at frequencies below 1000 Hertz. Thus, in the computational model at least, the analytic computation of phase can be used to represent timing for a subset of the auditory fibres. Another question that arises is: does biological tissue use analytic encoding?

To control phase by computing in the analytic domain, quadrature shifted excitations are included in the input suite on separate channels. To compute the quadrature shifted version of a finite bandwidth excitation, the Hilbert transform, $\tilde{x}(t)$, of an excitation, $x(t)$, may be approximated numerically as an FIR Hilbert transformer filter with frequency response

$$H(\Omega) = \begin{Bmatrix} -j, & 0 < \Omega \leq \pi \\ j, & -\pi < \Omega < 0 \end{Bmatrix}. \tag{2}$$

where Ω is the dimensionless frequency[9]. The appropriate set of weights is conceivably learnable by a neuronal processing element. Furthermore, if the frequency partitions are narrow, the derivative, $\dot{x}(t)$, divided by the center frequency of the band, ω_c, is a good enough approximation to the quadrature input in some cases, i.e.,

$$\tilde{x}(t) \approx \dot{x}(t)/\omega_c \approx j\sum_i(\omega_i/\omega_c)c(\omega_i)e^{j\omega_i t} \approx jx(t) \tag{3}$$

where the $c(\omega)$ are the complex fourier coefficients for the series approximation.

In well-known treatises on adaptive processing it has been shown that the addition of a second lag (a third tap) of the input can increase the adaptive beamformers ability to enhance the signal-to-noise ratio of a broadband signal in noise and interference[10]. The third tap is an inhibitory synapse relative to the first tap, since it produces the negative of the first tap input at the center frequency of the band.

2.3 Hopfield-type Optimization for Selective Spatial Focussing

An optimization scheme has been developed that has the capability to adaptively adjust timing/phasing to do spatial beamforming. An example architecture is illustrated in Fig. 1. The Hopfield crossbar circuit arrangement[11] is used as a computational kernel. The output voltages of the circuit are to represent the weights on an adaptive combiner[12]. In order to formulate the beamformer mechanism so that it responds adaptively to inputs, the minimum mean square error problem is posed and the currents and connectivities are solved for as functions of the inputs. The resulting expressions are

$$connectivity\ T_{ij}(t) = -\frac{1}{\tau}\int_{t-\tau}^{t} x_i(\eta)x_j(\eta)d\eta\ ,\ T_{ii} = 0 \quad (4)$$

$$ion\ flow\ I_i(t) = \frac{1}{\tau}\int_{t-\tau}^{t} x_i(\eta)h(\eta+\tau-t)d\eta - \frac{1}{2}v_i(t-\tau)\int_{t-\tau}^{t} x_i(\eta)x_i(\eta)d\eta \quad (5)$$

where τ is a response latency period, and $v_i(t-\tau)$ is the output amplitude at the end of the previous epoch from the ith element. In the case of discrete time-step simulations, the expectation value is usually evaluated by summing .

The performance of the Crossbar Adaptive Beamformer (CABF) was validated against composite sounds of a real sonar scene impinging upon a spatially complex array. The data were obtained from the Sonar Thinned Random Array Program (STRAP). Fig. 2 depicts the spatial arrangement of 11 sonobuoys that were dropped in the Atlantic ocean. A known source was active at a distance of approximately 10 miles. It consisted of two frequencies, seven and eleven Hertz. Figs. 3 and 4 show spectral densities from various channels. Notice the inconsistency across the channels.

The temporal recordings made at these buoys were played into the beamformer. Fig. 5 shows the adapted sensitivity of the CABF as a function of time. The CABF is correctly attending the desired signal at approximately 41 degrees. These results are very good when you consider that no spectral preprocessing was performed, i.e., the desired signal was still mixed with the other interfering components at a level of approximately -20dB with respect to some higher frequency components (Fig. 3). More tests are being performed in scenarios wherein interfering signals are arriving concurrently with the signal of interest and from a variety of directions (see **Mutual Inhibition** below).

2.4 Adaptive Temporal Sifting

It has been demonstrated by many studies and by our own experience listening to monaural radio sets that the human auditory system need not have spatial cues in order to sort out sounds that are simultaneously incident on our ears. To give this sorting capability to a processor, a temporal sifting procedure may be formulated using an augmented form of the Kohonen self-organization procedure[13]. The modified learning rule allows temporary storage of multi-dimensional n-vectors[14] that represent the average vectors of statistically meaningful groupings or classifications of the input vectors. The action of the so-called Multi-vector Adaptive Beamformer (MABF) is pictorially represented in Fig. 6. Temporal sifting and short-term memory formation is accomplished according to

$$W_i^{new} = W_i^{old} + \alpha(\vec{x}_k - \vec{c}_{ik})\Lambda\vec{d}_{ik} \quad (6)$$

where W_i is the "weight plane", expressed as a bi-vector in this case, of the ith processing element (PE) of a layer of PEs that receives a fan-out of the inputs, α is the learning rate, $\vec{c}_{ik}$ is the projection of the kth input vector, $\vec{x}_k$, onto W_i, normalized to unit length, $\vec{d}_{ik} = \overline{\vec{x}_k \cdot W_i^{old}}$ (the bar denotes normalization), and the symbol Λ denotes the wedge product. For the case of temporal learning, the input vectors are formed from a tapped delay line.

2.5 Quasi-recursive and Hebbian characteristics

The functional qualities of continuity, accommodation, and memory are supported by quasi-recursive (QR) and Hebbian arrangements whereby the adaptive mechanisms receive feedback from the output of the total adaptive process. Both types are depicted in the system building blocks in figs. 7 and 8. They are distinguishable by the connections to the adaptive mechanism.

The QR mechanism provides behavior somewhat analogous to the flip flop that is used in digital finite state machines. In this case however there are an infinite number of possible states, dependent upon the exemplar that is being presented and the content of the stimulus field. Thus, if a quasi-recursive NABF (QR-NABF) finds what it is looking for in the sensory excitation, it locks on to it, forming a quite stable state that persists even if the desired excitation is temporarily interfered with. Thus, the QR-NABF forms a short-/medium-term memory and, what is more, coincidentally attends and verifies the occurrence of the desired excitation. An architecture for the implementation of QR-NABFs is discussed below. The equations (4) and (5) apply with each occurrence of x_i replaced by y_i, where the multiple outputs, y_i, are each phase-centered on the ith sensor:

$$connectivity\ T_{ij}(t) = -\tfrac{1}{\tau}\int_{t-\tau}^{t} y_i(\eta)y_j(\eta)d\eta\,,\ T_{ii} = 0 \qquad (7)$$

$$ion\ flow\ I_i(t) = \tfrac{1}{\tau}\int_{t-\tau}^{t} y_i(\eta)h(\eta+\tau-t)d\eta - \tfrac{1}{2}y_i(t-\tau)\int_{t-\tau}^{t} x_i(\eta)y_i(\eta)d\eta \qquad (8)$$

The Hebbian arrangement correlates the feedback from the output with the corresponding inputs to determine the synaptic modification. Equations (4) and (5) apply with changes to reflect the Hebb-like learning rule:

$$connectivity\ T_{ij}(t) = -\tfrac{1}{\tau}\int_{t-\tau}^{t} x_i(\eta)y_j(\eta)d\eta\,,\ T_{ii} = 0 \qquad (9)$$

$$ion\ flow\ I_i(t) = \tfrac{1}{\tau}\int_{t-\tau}^{t} y_i(\eta)h(\eta+\tau-t)d\eta - \tfrac{1}{2}y_i(t-\tau)\int_{t-\tau}^{t} x_i(\eta)y_i(\eta)d\eta \qquad (10)$$

2.6 Mutual inhibition

In order to utilize resources efficiently and have the capability of perceptually separating mixtures of stimuli the neural elements must interact in a way that forms an organizational network. A sensory hierarchy is one such organization (as it turns out, the most easily implemented). Building blocks for a hierarchical assembly are represented diagrammatically in Fig. 7 and Fig. 8. The "beam group" symbols each represent a set of beams that are derived by displacing the phase reference to particular sensors or channels. Thus, a beam group has an output channel for each input channel. The outputs of each module goes to the inputs of a similar module, and so on. In this kind of arrangement, elements that are responding to a particular stimulus inhibit other elements lower in the hierarchy from responding to it and thereby free them to respond to other stimuli that may be concurrently active.

A neurobiological correlate to this action may be suggested by recent work regarding the inferior-temporal (IT) cortex of the rhesus monkey[15]. It was found that some cells in that region have a reduced response over time to repeated stimuli while maintaining substantial response to new stimuli. It could be hypothesized that other cells are selecting the repeated stimuli and inhibiting their propagation to the cells in IT, thereby forming a novelty filter effect.

A hierarchical beamforming approach has been used for similar purposes. The inhibitory effect comes about through the formation of notch beams that pass the excitation to lower levels in the hierarchy. First, a quasi-recursive beamformer enhances its sensitivity to a particular excitation as described previously. Next, a combination of inhibitory and excitatory connections to another element produces the notch beam, i.e., it produces a minimization of response in the dimensional ranges where the initial elements response is maximized.

In Figs. 9 and 10, parts a and b show the NABF receptivity as a function of the angle of incidence at the first (highest) and second levels of the hierarchy, respectively. Two identical signals are incident at approximately 35 and -30 degrees. In Fig. 9, the signal onsets are simultaneous and the NABF pair are confused. In Figs. 10 and 11, one signal onset is delayed approximately 10 milliseconds from the other. In each case, the receptivity of the highest level NABF is focussed on one angle of incidence, while the receptivity of the second level beamformer is maximized at the other angle of incidence. Thus, the confusion evident in Fig. 9 is eliminated. Recursion is applied in Fig. 11 but not in figs. 9 or 10.

2.7 Adaption of receptive field within internal representations

If neurons can adjust their receptive fields as the ABF paradigm suggests (by adaptively weighting synapses) then there may be attentional shifting within the internal physical representations generated by sensory systems. A phenomenon that has been observed recently in visual processing in the parietal cortex of monkeys[16] suggests that neurons have the ability to coordinate representational shifts with movements of the eye. In the context of the auditory system, a related capability may account for pitch-independent recognition of a musical instrument. Thus, in a cognitive sensory system model, the ABF paradigm will be utilized to realize active recognition memory that can move the receptive fields of its elements along internal representations. With regard to hearing, the action of the cochlear partition contributes to an internal representation that preserves patterns of excitation due to the logarithmic best-frequency dependence as a function of distance along the basilar membrane.

3. COGNITIVE SENSORY SYSTEM

The system architecture is very important, not only because it provides for the funnelling of outputs of one process into the inputs of another, but also because the architecture supports multidimensional encoding transformations, e.g., topological mappings that have important relationships to external space, or that allow reduction of the dimensionality of information to be axonally propagated. In addition, the somewhat specialized sub-processes of the system are interdependent and require robust interconnection. Therefore, the neural computation approach is ideal and, along with the considerations reviewed in the INTRODUCTION and MECHANISM sections, leads to a plausible processing scheme for selectively attending partials of complex sensory excitations.

There is an issue of fundamental importance raised by a cortical beamforming/recognition approach with regard to generation of exemplars used for attentionally directed segmentation; the issue is whether or not an exemplar is generated in cortex and passed to some more peripheral part to the sensory system (perhaps an intermediate stage) via efferents. This would facilitate the attentional function at early stages as has been observed and it would also facilitate internally generated "visualization" about sensory experience, i.e., it would facilitate the ability to visualize some sensory happening. This would happen without an immediate incoming sensory prompt and would be generated out of associations made during thought causing the enlistment of sensor areas for visualization by the production of efference to intermediate and/or peripheral sensory areas. In either case, the efference is produced by associations made in cortex ... by association between memory and afferent sensory activity in one case and between memory and thought in the other.

In the attentional effect produced by the beamformer, the efference serves as an exemplar. Thus, a resonance can be achieved through interaction of sensory activation, associational memory, and thought (symbolic processing as can be generated by expert systems) to achieve focussing on portions of the sensory activity remembered or thought (hypothesized) to be mission-relevant (or survival-relevant).

In experiments related to this issue, Metzner at Scripps Institute of Oceanography, University of California, reported an efference within neural tissue whereby transmissions of the horseshoe bat are compared with echoes in order to sense the Doppler and adjust its emission frequency accordingly. This is in contrast to the idea that the bat listens to its own emission in order to generate the exemplar. This brings up the question whether the cortical oscillations being reported in the literature are active generators of "efference."

Furthermore, spontaneous otoacoustic emissions have been measured in the human ear canal, and the models considered by Zwicker and Peisl (1990) which try to explain this include lateral coupling and nonlinear active feedback analogous to those proposed for the neurobionic beamformer. It may be that the feedback in the beamformer matrix is relevant to feedback observed at the cochlear level in the auditory system.

A conceptual overview and some key elements of a comprehensive processing scheme are depicted in figures 12 and 13, respectively. The conceptual overview is a simplified representation that includes four principal functions: (1) the partitioning function, (2) the selection function, (3) position and motion determination, and (4) recognition. In reality, these functions are not performed separately. They are provided by the interacting elements of the processing scheme.

The key elements of the processing scheme are: (1) multiple band filtering, (2) binaural correlation, (3) spatial adaptive beamforming, and (4) temporal adaptive beamforming. In practice, multiple-band filtering corresponding to the cochlear filtering indicated in figure 13 is performed using a scaled-wavelet formulation, providing a spread of bandwidths associated with the various best-frequencies. It is recognized that this model cannot account for the sharpness of the cochlear response function near the best frequency[18]. Spatial mappings have been observed in the colliculus in some vertebrates[19,20] and in cortical field AI of the cat .

The processor contains a band-wise spatial mapping that receives excitations from the partitioned output of the cochlear process, i.e., the array of bandpass filters. The spatial mapping is supported by the confluence of afferent excitation from the sensors at intermediate computational nuclei (labelled SOC in Fig. 13). An adaptive mechanism supplies attentional focussing while the excitations are spatially mapped, creating areas of enhanced activity. This function may be a correlate of the activity of the dorsal cochlear nucleus (DCN). Intermediate between the cochlear processing and the band-wise spatial mapping is an adaptive spatial process (not depicted) provided by the NABF. The darkened areas represent those attended (emphasized) by the NABF. Thus the spatial layer acts as a sieve, passing attended stimulus partials.

The spatial mappings can be related to the beamformer sensitivity maps of figures 9 through 11 where a single row of the spatial map as a function of time is plotted contiguously down the page. These maps may be thought to represent the activity of a layer of beamformers with relatively fixed directional preferences. What is the purpose of forming a topological organization of the beamformers? The topological mapping creates an organization by which the cells for the various auditory bands which respond to a given object in space are close together. This simplifies the projection of the output of the spatial neurons to the cortical area where recognition is accomplished. This organization is also beneficial in the digital signal processing application, though the units are not actually arranged spatially but are arranged by ordinal number instead.

Notice that a loop has been formed, because the output of the spatial map projects as input to the recognition area, the output of which was utilized in the formation of the spatial map. In the biological case, it is not clear whether this system constantly feeds back on itself or if there is an afferent wave of activity followed by an efferent wave or vice versa. In the case of the computational model, it can be done either way and perhaps an investigation of this will lead to some conclusions. It could be that the loop leads to oscillations in some circumstances. If it does, the relationship of the oscillations may be studied in light of recent observations[21].

In the computational model, the projections from the spatial map are input to a MABF process. The overall action of the recognition MABF is to segment and identify patterns of temporal activity across the auditory bands which are established in the cochlea. Each spatial stimulus segment is again segmented temporally according to memory by creating a time dependent sensitivity. The MABF attempts to create a stimulus partial which matches the temporal characteristics of each band, the total effect being to match the spectral content as a function of time, including relative phase variations, of an [illegible] memory [illegible] the spatially oriented spectral-band inputs as a basis. Recognition depends upon a [illegible] of responses across the bands, i.e., the temporal qualities of all the individual frequency bands is being assessed simultaneously. Frequency modulation in the stimulus will appear as recognizable temporal variation in the bands. In the training mode, memories are established as a set of weightings.

The main function of the recognizer is to attend memory according to the stimulus. Only the temporally varying activities of the **attended** spatial segments elicit memories, because they are stronger. Initially, however, the system may not be attentionally focussed and the performance of the NABF on composite waveforms becomes important. In some cases, individual sounds may not be discerned without intervention of a thought process.

When a memory is elicited, a partial of the stimulus is produced through the action of the temporal beamformer, i.e., when a beamformer wins then the temporal vector associated with that memory is considered a partial of the stimulus (a significant one). This partial is fed back to the spatial mapping process, resulting in attention to or a focussing upon the spatial sector from where the partial came.

4. CONCLUSIONS

Adaptive "beamforming" can play multiple roles in comprehensive sensory processing systems and serves as a paradigm that applies as well to patterns as are observed in neuronal responses in the cochlear nucleus and superior colliculus as it does to simple spatial and temporal filtering patterns. Some neural arrangements for adaptive beamforming outlined here have been demonstrated to function as expected on sea-test data and in the laboratory. Building blocks for groups of mutually inhibitory beamformers were also outlined, and the operation of a pair of them was demonstrated. They were shown to respond correctly under the conditions of simultaneous incidence of multiple identical (or very similar) stimuli, wherein a single NABF would be confused.

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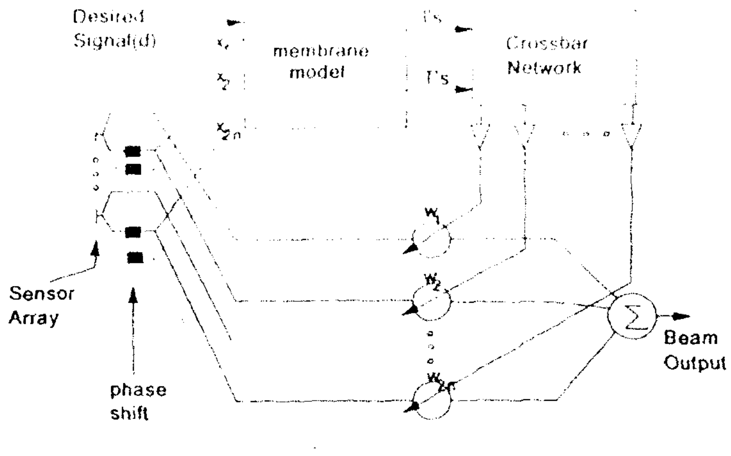

Fig. 1. An adaptive beamforming architecture that uses the Hopfield arrangement for solving the optimization problem. The optional "third tap," which is an inhibitory connection relative to the first tap, is represented in dashed lines.

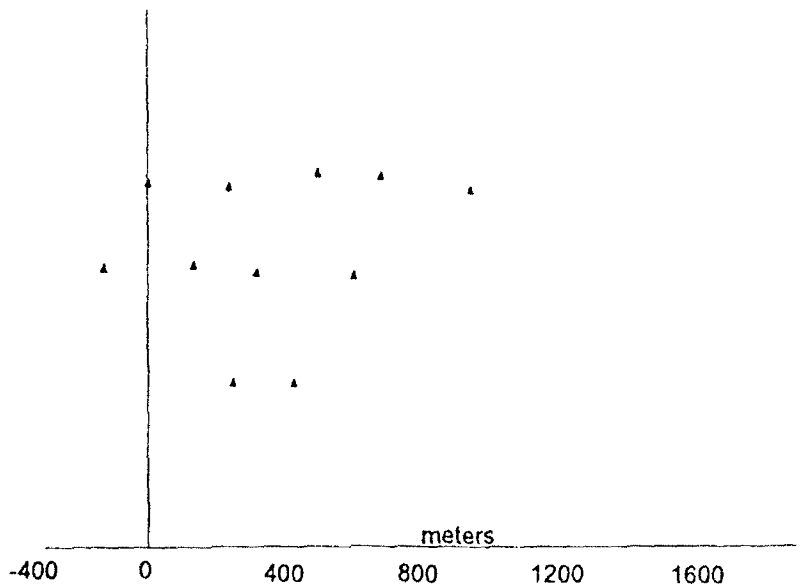

Fig. 2. The deployment pattern for the 11 buoys relevant to the test data from the Sonar Thinned Random Array Program (STRAP).

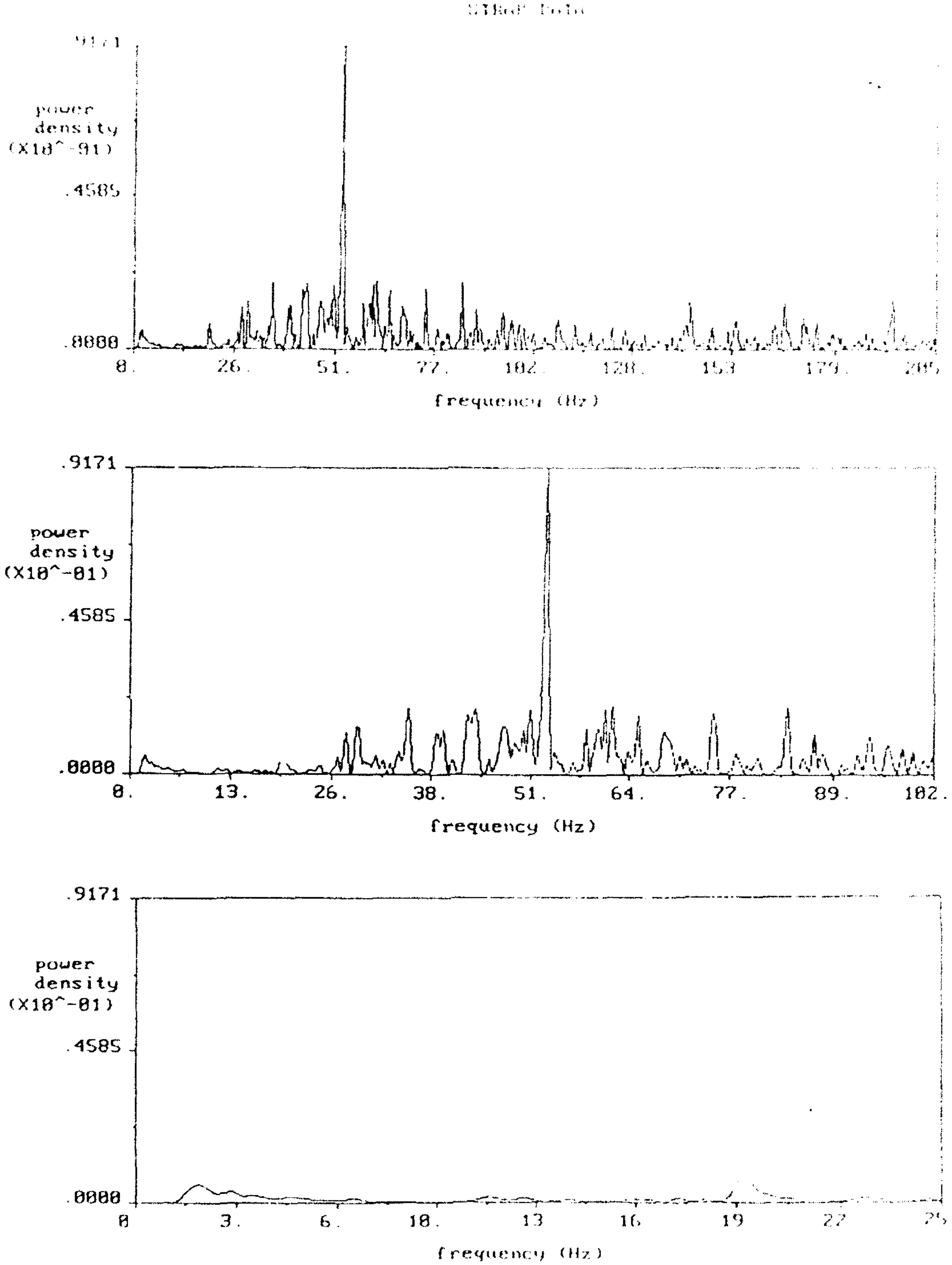

Fig. 3. Spectral density plots for the data from the channel 1 buoy, varying frequency scale. The signal of interest is a combination of 7 and 11 Hertz.

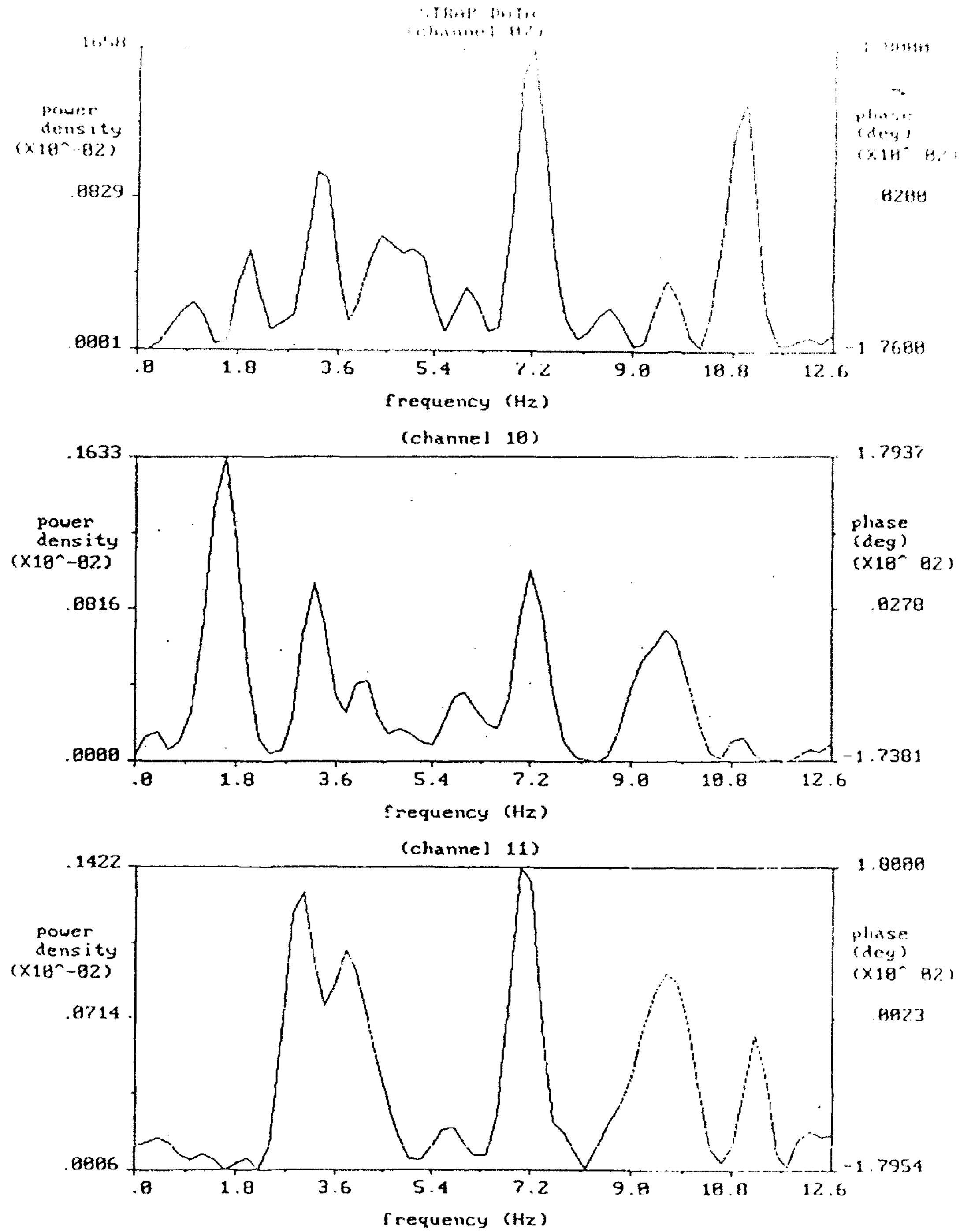

Fig. 4. Spectral density plots for three different buoys; fixed frequency scale. The region of interest is emphasized. Note variation from buoy to buoy.

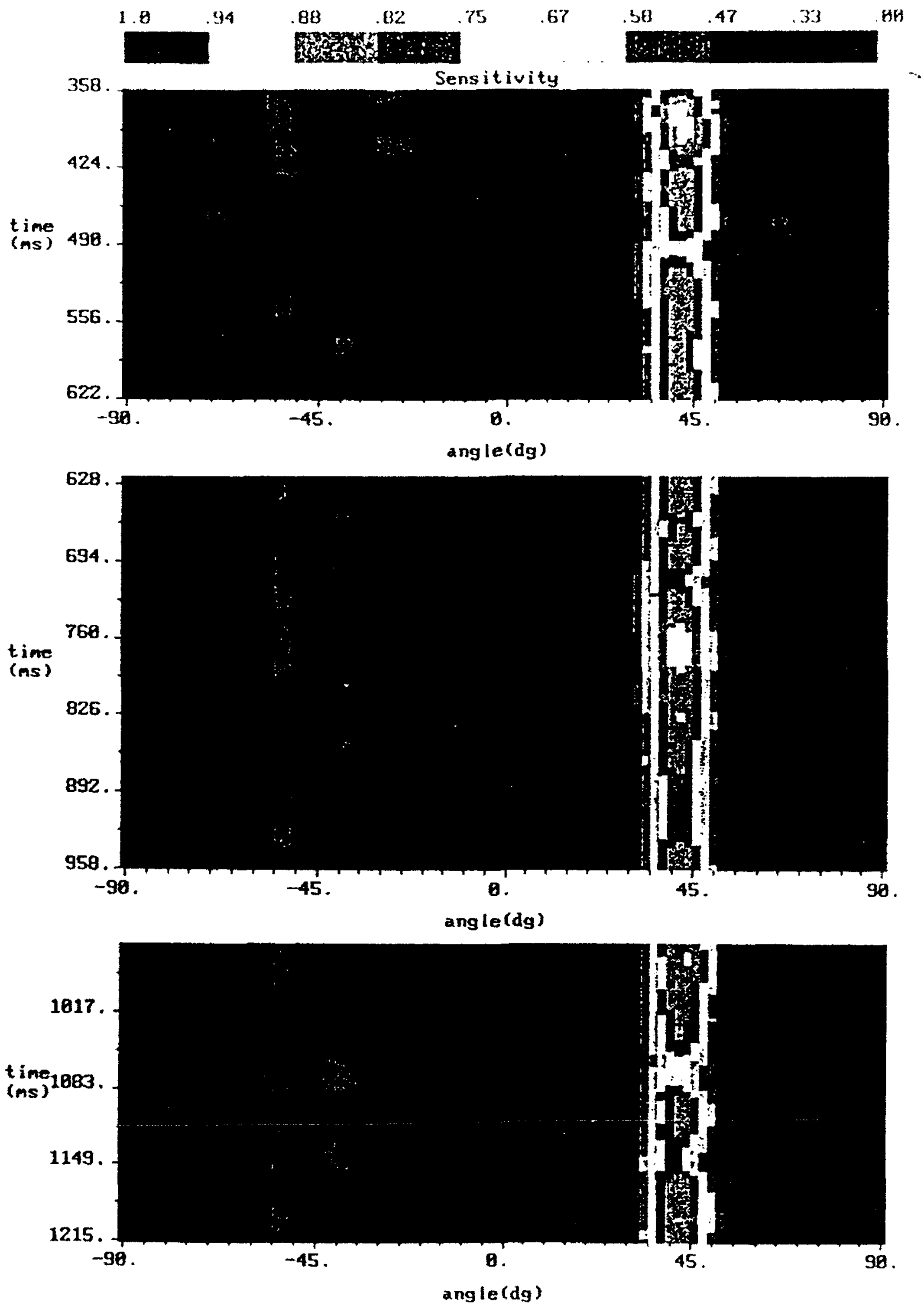

Fig. 5. The automatically adapted beam sensitivity; the beamforming result with no pre-filtering.

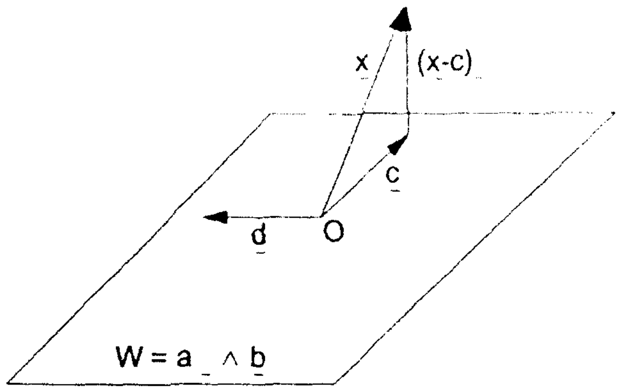

Fig. 6. Illustration of constructs relevant to a bi-vector instantiation of the multi-vector beamforming paradigm.

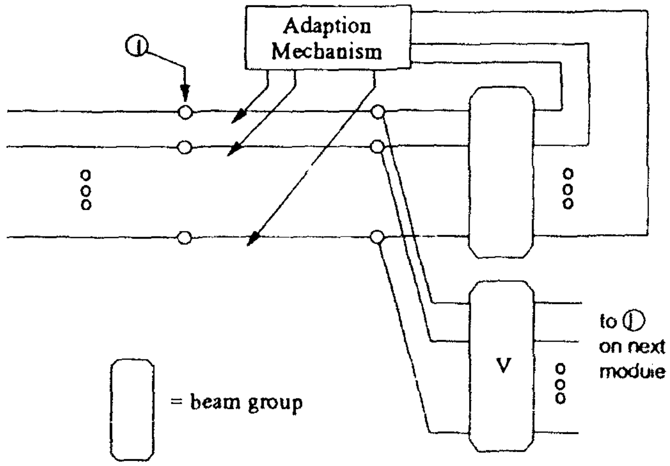

Fig. 7. Illustration of the quasi-recursive (QR) computational module for hierarchical processing.

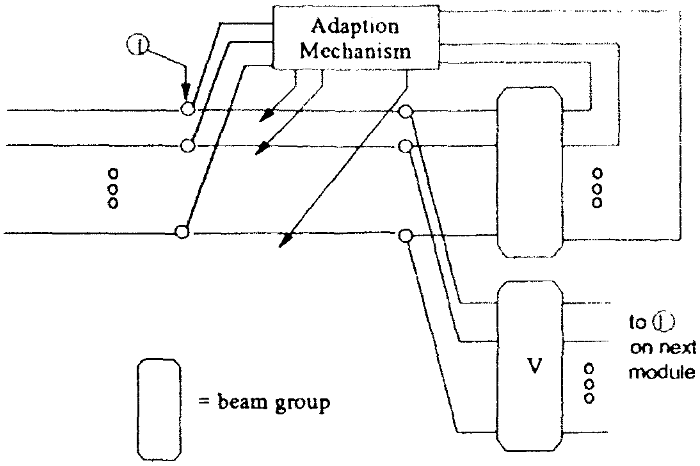

Fig. 8. Hebbian module for hierarchical interaction.

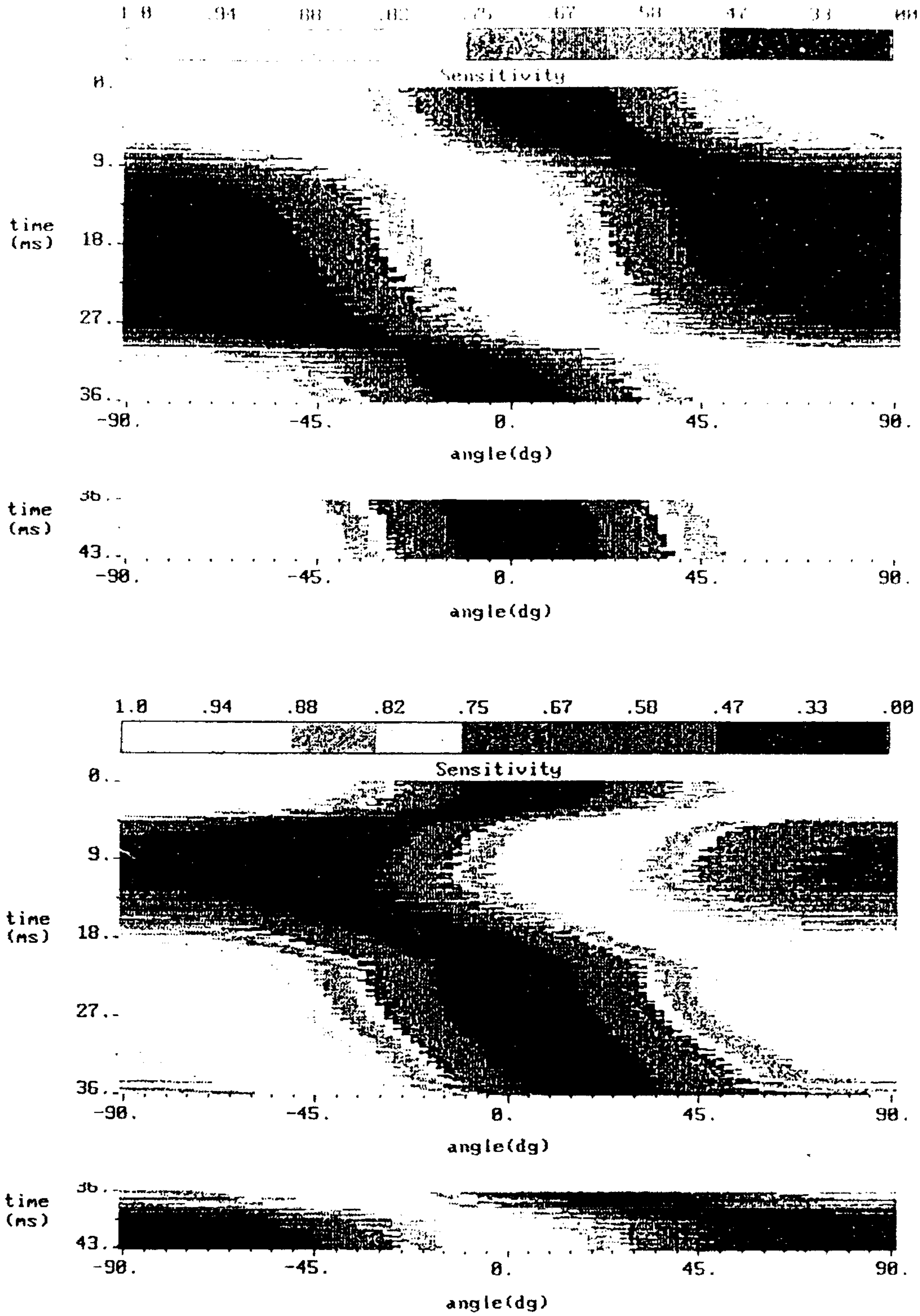

Fig. 9. First (a) and second (b) level hierarchical beamformers. They are confused when two identical stimuli are incident from 35 and -30 degrees and with simultaneous onset.

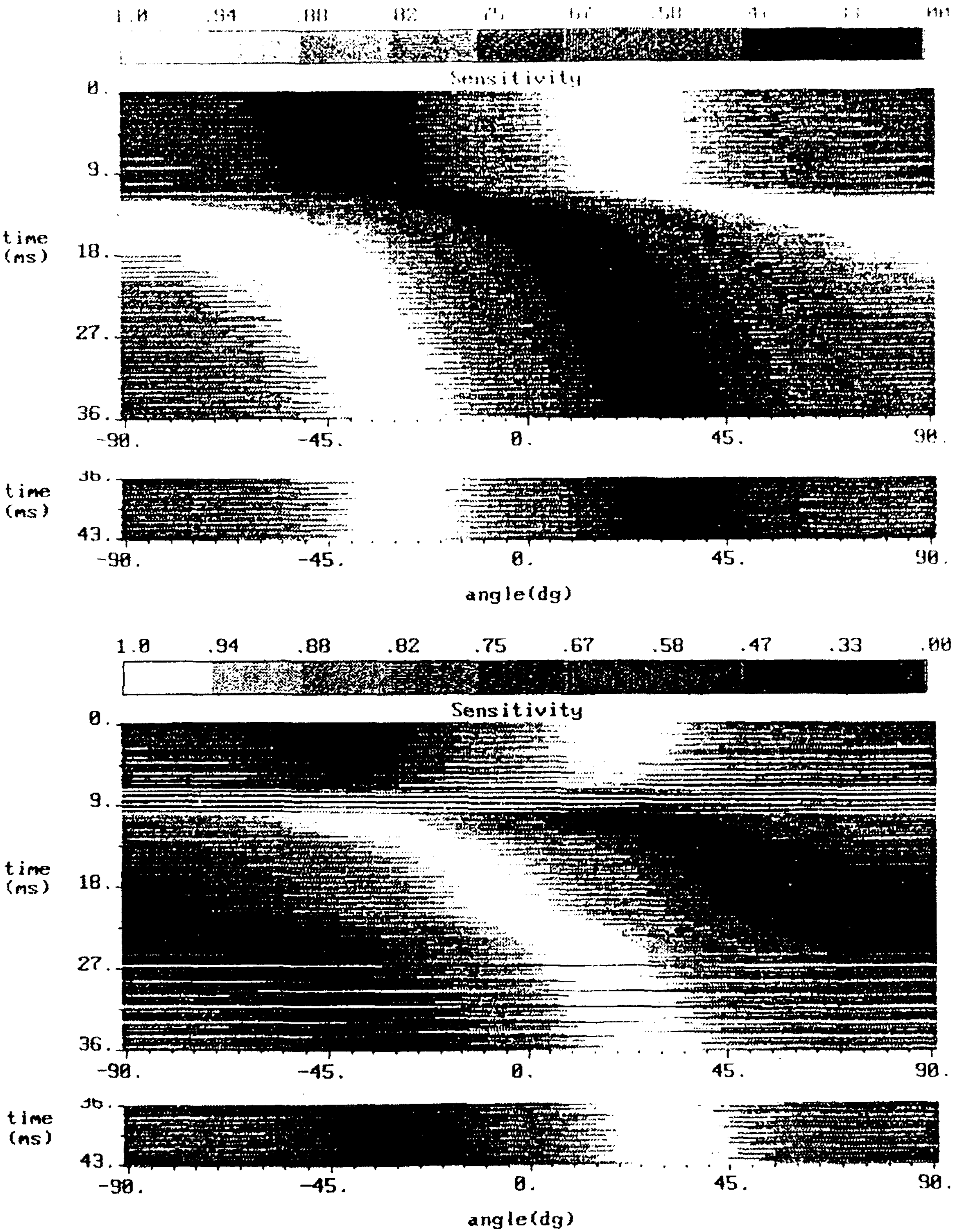

Fig. 10. First (a) and second (b) level hierarchical beamformers. Each claims a different stimuli when the onsets are different by approximately 10 milliseconds.

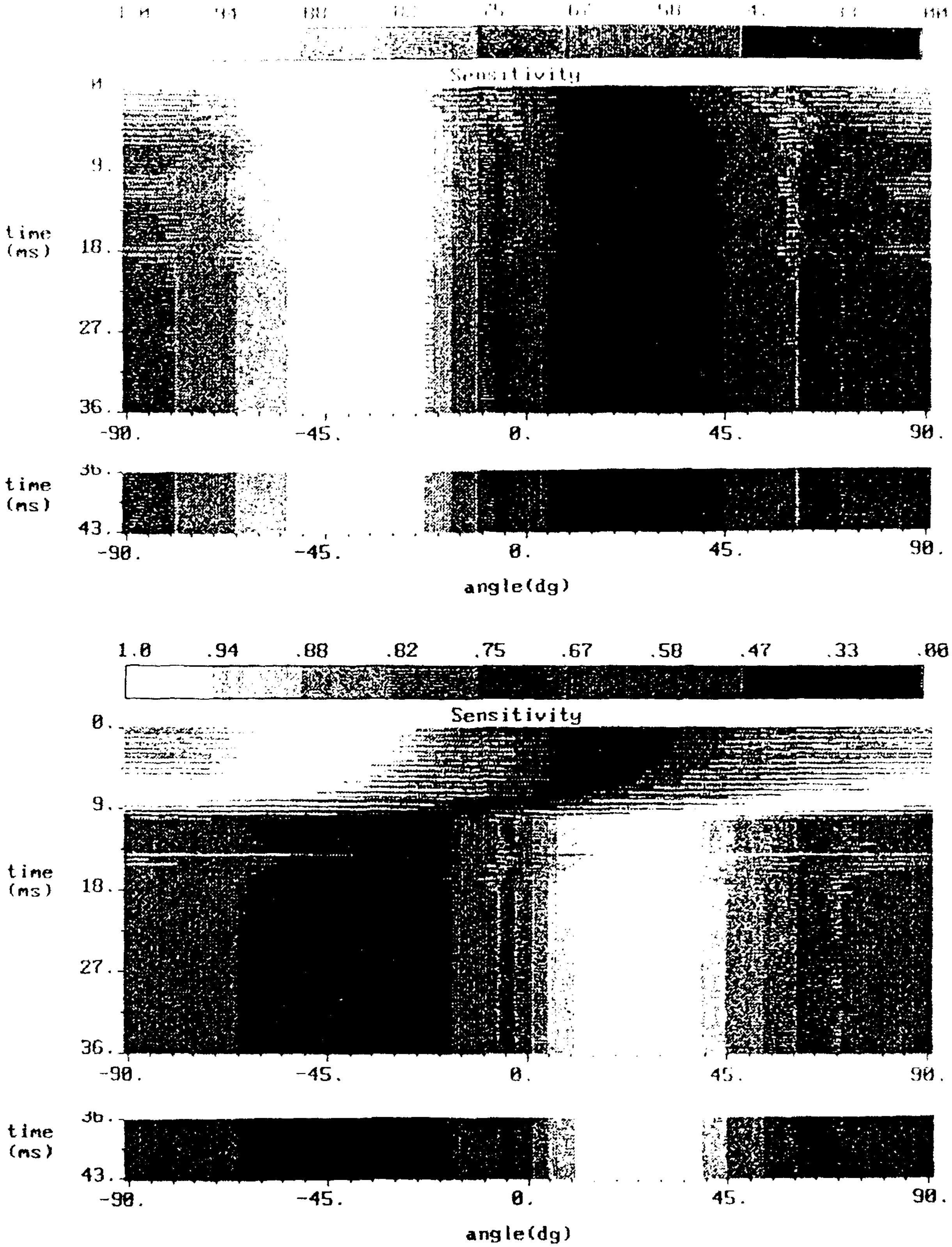

Fig. 11. First (a) and second (b) level hierarchical beamformers. Same as Fig. 10 except beamformers are QR. The angle scale is switched from Fig. 10.

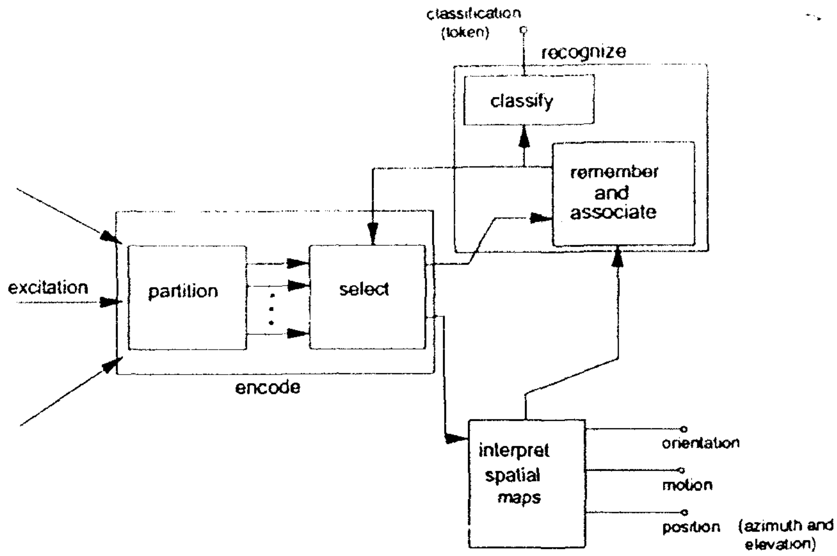

Fig. 12. Conceptual overvie of the sensory processing architecture.

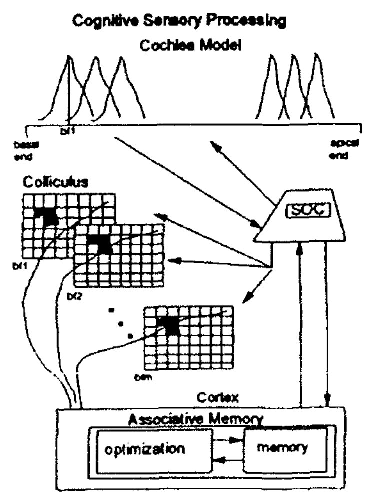

Fig. 13. An architecture for cognitive sensory processing with auditory system analogues.